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A review on the prediction of building energy consumption

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The energy performance in buildings is influenced by many factors, such as ambient weather conditions, building structure and characteristics, the operation of sub-level components like lighting and HVAC systems, occupancy and their behavior. This complex situation makes it very difficult to accurately implement the prediction of building energy consumption. This paper reviews recently developed models for solving this problem, which include elaborate and simplified engineering methods, statistical methods and artificial intelligence methods. Previous research work concerning these models and relevant applications are introduced. Based on the analysis of previous work, further prospects are proposed for additional research reference.

Contents

1. Introduction

In Europe, buildings account for 40% of total energy use and 36% of total CO_2 emission [1]. The prediction of energy use in buildings is therefore significant in order to improve their energy performance, with the aim of achieving energy conservation and reducing environmental impact. However, the energy system in buildings is quite complex, as the energy types and building types vary greatly. In the literature, the main energy forms considered are heating/cooling load, hot water and electricity consumption. The most frequently considered building types are office, residential and engineering buildings, varying from small rooms to big estates. The energy behavior of a building is influenced by many factors, such as weather conditions, especially the dry-bulb temperature, the building construction and thermal property of the physical materials used, the occupancy and their behavior, sub-level components such as lighting, HVAC (Heating, Ventilating, and Air-Conditioning) systems, their performance and schedules.

Due to the complexity of the problem, precise consumption prediction is quite difficult. In recent years, a large number of approaches to prediction, either elaborate or simplified, have been proposed and applied to a broad range of problems. This research work has been carried out in the process of building design, operation or retrofit of contemporary buildings, varying from building's sub-system analysis to regional or national level modeling. Predictions can be performed on the whole building or sub-level components by thoroughly analyzing each influencing factor or approximating the usage by considering several major factors.

This paper reviews the recent work related to the modeling and prediction of building energy consumption. These methods include engineering, statistical and artificial intelligence methods. The most widely used artificial intelligence methods are Artificial

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Neural Networks (ANNs) and Support Vector Machines (SVMs). In 2003 and 2010, Krarti and Dounis respectively provided two overviews of artificial intelligence methods in the application of building energy systems [2,3]. Our paper especially focuses on the prediction applications. To even further enrich the content and provide the readers with a complete view of various prediction approaches, this paper also reviews engineering and statistical methods. Moreover, there are also some hybrid approaches which combine some of the above models to optimize predictive performance, such as [4–7]. In this paper, we globally describe the applications, models, related problems such as data pre-processing, and possible future prospects.

The content is organized as follows. Section 2 reviews the recent studies by classifying them according to the model used. Section 3 presents the discussion and future research points and Section 4 presents our conclusions.

2. The prediction methods

2.1. Engineering methods

The engineering methods use physical principles to calculate thermal dynamics and energy behavior on the whole building level or for sub-level components. They have been adequately developed over the past fifty years. These methods can be roughly classified into two categories, the detailed comprehensive method and the simplified method. The comprehensive methods use very elaborate physical functions or thermal dynamics to calculate precisely, step-by-step, the energy consumption for all components of the building with building's and environmental information, such as external climate conditions, building construction, operation, utility rate schedule and HVAC equipment, as the inputs. In this paper, we concentrate on the global view of models and applications, while the details of these computational processes are far beyond the purpose of this review. Readers may refer to [8] for calculation details. For HVAC systems, in particular, the detailed energy calculation is introduced in [9]. The ISO has developed a standard for the calculation of energy use for space heating and cooling for a building and its components [10].

Hundreds of software tools have been developed for evaluating energy efficiency, renewable energy, and sustainability in buildings, such as DOE-2, EnergyPlus, BLAST, ESP-r. Some of them have been widely used for developing building energy standards and analyzing energy consumption and conservation measures of buildings. Surveys of these tools are performed in [11,12]. For readers' information, the U.S. Department of Energy (DOE) maintains a list of almost all the simulation tools [13], which is constantly updated.

Although, these elaborate simulation tools are effective and accurate, in practice, there are some difficulties. Since these tools are based on physical principles, to achieve an accurate simulation, they require details of building and environmental parameters as the input data. On one hand, these parameters are unavailable to many organizations, for instance, the information on each room in a large building is always difficult to obtain. This lack of precise inputs will lead to a low accurate simulation. On the other hand, operating these tools normally requires tedious expert work, making it difficult to perform and cost inefficient. For these reasons some researchers have proposed simpler models to offer alternatives to certain applications.

Al-Homoud [11] reviewed two simplified methods. One is degree day method in which only one index, degree day, is analyzed. This steady-state method is suitable for estimating small buildings' energy consumption where the envelope-based energy dominates. The other one is bin, also known as temperature frequency method, which can be used to model large buildings where internally generated loads dominate or loads are not linearly dependent on outdoor/indoor temperature difference.

Weather conditions are important factors to determine building energy usage. These take many forms, such as temperature, humidity, solar radiation, wind speed, and vary over time. Certain studies are conducted to simplify weather conditions in building energy calculations. White and Reichmuth [14] attempted to use average monthly temperatures to predict monthly building energy consumption. This prediction is more accurate than standard procedures which normally use heating and cooling degree days or temperature bins. Westphal and Lamberts [15] predicted the annual heating and cooling load of non-residential buildings simply based on some weather variables, including monthly average of maximum and minimum temperatures, atmospheric pressure, cloud cover and relative humidity. Their results showed good accuracy on low mass envelope buildings, compared to elaborate simulation tools such as ESP, BLAST, DOE2, etc.

As well as weather conditions, building characteristic is another important yet complex factor in determining energy performance.

Yao and Steemers [4] developed a simple method of predicting a daily energy consumption profile for the design of a renewable energy system for residential buildings. The total building energy consumption was defined as the summation of several components: appliances, hot water, and space heating. For each component, a specific modeling method was employed. For instance, to model electric appliances, they used the average end-use consumption from large amounts of statistical data. While modeling space heating demand, a simplified physical model was applied. Since the average value varies seasonally, this method predicts energy demand for one season at a time.

By adopting this divide-and-sum concept, Rice et al. [16] simplified each sub-level calculation to explain the system level building energy consumption. In the project "Updating the ASHRAE/ACCA Residential Heating and Cooling Load Calculation Procedures and Data" (RP-1199), Barnaby and Spitler [17] proposed a residential load factor method, which is a simple method and is tractable by hand. The load contributions from various sources were separately evaluated and then added up. Wang and Xu [5] simplified the physical characteristics of buildings to implement the prediction. For building envelops, the model parameters were determined by using easily available physical details based on the frequency characteristic analysis. For various internal components, they used a thermal network of lumped thermal mass to represent the internal mass. Genetic algorithm was used to identify model parameters based on operation data. Yik et al. [18] used detailed simulation tools to obtain cooling load profiles for different types of buildings. A simple model, which is a combination of these detailed simulation results, was proposed to determine the simultaneous cooling load of a building.

Calibration is another important issue in building energy simulation. By tuning the inputs carefully, it can match the simulated energy behavior precisely with that of a specific building in reality. Pan et al. [19] summarized the calibrated simulation as one building energy analysis method and applied it to analyze the energy usage of a high-rise commercial building. After steps of repeated calibration, this energy model showed high accuracy in predicting the actual energy usage of the specified building. A detailed review of calibration simulation is provided in [20]. Since calibration is a tedious and time-consuming work, we can see that doing accurate simulation by a detailed engineering method is of high complexity.

We note that there is no apparent boundary between the simplified and elaborate models. It is also possible to do simplified simulation with some comprehensive tools, such as EnergyPlus [21]. Suggested by AI-Homoud, if the purpose is to study trends, compare systems or alternatives, then simplified analysis methods

might be sufficient. In contrast, for a detailed energy analysis of buildings and sub-systems and life cycle cost analysis, more comprehensive tools will be more appropriate [11].

2.2. Statistical methods

Statistical regression models simply correlate the energy consumption or energy index with the influencing variables. These empirical models are developed from historical performance data, which means that before training the models, we need to collect enough historical data. Much research on regression models has been carried out on the following problems. The first is to predict the energy usage over simplified variables such as one or several weather parameters. The second is to predict some useful energy index. The third one is to estimate important parameters of energy usage, such as total heat loss coefficient, total heat capacity and gain factor, which are useful in analyzing thermal behavior of building or sub-level systems.

In some simplified engineering models, the regression is used to correlate energy consumption with the climatic variables to obtain an energy signature [22–24]. Bauer and Scartezzini [22] proposed a regression method to handle both heating and cooling calculations simultaneously by dealing with internal as well as solar gains. Ansari et al. [25] calculated the cooling load of a building by adding up the cooling load of each component of the building envelope. Each sub-level cooling load is a simple regression function of temperature difference between inside and outside. Dhar et al. [26,27] modeled heating and cooling load in commercial buildings with outdoor dry-bulb temperature as the only weather variable. A new temperature-based Fourier series model was proposed to represent nonlinear dependence of heating and cooling loads on time and temperature. If humidity and solar data is also available, they suggested using the generalized Fourier series model since it has more engineering relevance and higher prediction ability. Also taking dry-bulb temperature as the single variable for model developing, Lei and Hu [28] evaluated regression models for predicting energy savings from retrofit projects of office buildings in a hot summer and cold winter region. They showed that a single variable linear model is sufficient and practical to model the energy use in hot and cold weather conditions. Ma et al. [29] integrated multiple linear regression and self-regression methods to predict monthly power energy consumption for large scale public buildings. In the work of Cho et al. [30], the regression model was developed on 1-day, 1-week, 3-month measurements, leading to the prediction error in the annual energy consumption of 100%, 30%, 6% respectively. These results show that the length of the measurement period strongly influences on the temperature dependent regression models.

Concerning the prediction of energy index, Lam et al. [31] used Principle Component Analysis (PCA) to develop a climatic index Z with regard to global solar radiation, dry- and wet-bulb temperature. They found that Z has the same trend as simulated cooling load, HVAC and building energy use. This trend was obtained from the analysis of correlation by a linear regression analysis. The model was developed based on the data from 1979 to 2007. Ghiaus [32] developed a robust regression model to correlate the heating loss on the dry-bulb temperature by using the range between the 1st and the 3rd quartile of the quantile–quantile plot which gives the relation of these two variables.

Jiménez and Heras [33] used the Auto-Regressive model with eXtra inputs (ARX) to estimate the U and g values of building components. Kimbara et al. [34] developed an Auto-Regressive Integrated Moving Average (ARIMA) model to implement on-line prediction. The model was first derived on the past load data, and was then used to predict load profiles for the next day. ARIMA with eXternal inputs (ARIMAX) models have also been applied to some applications, predicting and controlling the peak electricity demand for commercial buildings [35] and predicting the power demand of the buildings [36]. In [36], Newsham and Birt put a special emphasis on the influence of occupancy, which can apparently increase the accuracy of the model.

Aydinalp-Koksal and Ugursal [37] suggested considering a regression-based method, called Conditional Demand Analysis (CDA), when we predict national level building energy consumption. In their experimental comparisons, CDA showed accurate predicting ability as good as neural networks and engineering methods, but was easier to develop and use. However, the drawback of the CDA model was lack of detail and flexibility, and it required a large amount of input information. CDA was also employed in the early work for analyzing residential energy consumption [38–40].

2.3. Neural networks

ANNs are the most widely used artificial intelligence models in the application of building energy prediction. This type of model is good at solving non-linear problems and is an effective approach to this complex application. In the past twenty years, researchers have applied ANNs to analyze various types of building energy consumption in a variety of conditions, such as heating/cooling load, electricity consumption, sub-level components operation and optimization, estimation of usage parameters. In this section, we review the previous studies and put them into groups according to the applications dealt with. Additionally, model optimization, such as pre-process of input data and comparisons between ANNs and other models, are highlighted at the end.

In 2006, Kalogirou [41] did a brief review of the ANNs in energy applications in buildings, including solar water heating systems, solar radiation, wind speed, air flow distribution inside a room, prediction of energy consumption, indoor air temperature, and HVAC system analysis.

Kalogirou et al. [42] used back propagation neural networks to predict the required heating load of buildings. The model was trained on the consumption data of 225 buildings which vary largely from small spaces to big rooms. Ekici and Aksoy [43] used the same model to predict building heating loads in three buildings. The training and testing datasets were calculated by using the finite difference approach of transient state one-dimensional heat conduction. Olofsson et al. [44] predicted the annual heating demand of a number of small single family buildings in the north of Sweden. Later, Olofsson and Andersson [45] developed a neural network which makes long-term energy demand (the annual heating demand) predictions based on short-term (typically 2–5 weeks) measured data with a high prediction rate for single family buildings.

In [46], Yokoyama et al. used a back propagation neural network to predict cooling demand in a building. In their work, a global optimization method called modal trimming method was proposed for identifying model parameters. Kreider et al. [47] reported results of a recurrent neural network on hourly energy consumption data to predict building heating and cooling energy needs in the future, knowing only the weather and time stamp. Based on the same recurrent neural network, Ben-Nakhi and Mahmoud [48] predicted the cooling load of three office buildings. The cooling load data from 1997 to 2000 was used for model training and the data for 2001 was used for model testing. Kalogirou [49] used neural networks for the prediction of the energy consumption of a passive solar building where mechanical and electrical heating devices are not used. Considering the influence of weather on the energy consumption in different regions, Yan and Yao [50] used a back propagation neural network to predict building's heating and cooling load in different climate zones represented by heating degree day and cooling

degree day. The neural network was trained with these two energy measurements as parts of input variables.

In the application of building electricity usage prediction, an early study [51] has successfully used neural networks for predicting hourly electricity consumption as well as chilled and hot water for an engineering center building. Nizami and Al-Garni [52] tried a simple feed-forward neural network to relate the electric energy consumption to the number of occupancy and weather data. González and Zamarreño [53] predicted short-term electricity load with a special neural network which feeds back part of its outputs. In contrast, Azadeh et al. [54] predicted the long-term annual electricity consumption in energy intensive manufacturing industries, and showed that the neural network is very applicable to this problem when energy consumption shows high fluctuation. Wong et al. [55] used a neural network to predict energy consumption for office buildings with day-lighting controls in subtropical climates. The outputs of the model include daily electricity usage for cooling, heating, electric lighting and total building.

ANNs are also used to analyze and optimize sub-level components behavior, mostly for HVAC systems. Hou et al. [56] predicted air-conditioning load in a building, which is a key to the optimal control of the HVAC system. Lee et al. [57] used a general regression neural network to detect and diagnose faults in a building's air-handling unit. Aydinalp et al. [58] showed that the neural network can be used to estimate appliance, lighting and space cooling energy consumption and it is also a good model to estimate the effects of the socio-economic factors on this consumption in the Canadian residential sector. In their follow-up work, neural network models were developed to successfully estimate the space and domestic hot-water heating energy consumptions in the same sector [59].

In [60,48], general regression neural networks were used for air conditioning set-back controlling, and for optimizing HVAC thermal energy storage in public and office buildings. Yalcintas et al. [61] used neural networks to predict chiller plant energy use of a building in a tropical climate. Later, they used a three-layer feed-forward neural network to predict energy savings in equipment retrofit [62]. Gouda et al. [63] used a multi-layered feed-forward neural network to predict internal temperature with easily measurable inputs which include outdoor temperature, solar irradiance, heating valve position and the building indoor temperature.

Building energy performance parameters can be estimated by neural networks. In [64–67], the authors estimated the total heat loss coefficient, the total heat capacity and the gain factor which are important for a reliable energy demand forecast. The method is based on an analysis of a neural network model that is trained on simple data, the indoor/outdoor temperature difference, the supplied heat and the available free heat. Kreider et al. [47] reported results of recurrent neural networks on hourly energy consumption data. They also reported results on finding the thermal resistance, *R*, and thermal capacitance, *C*, for buildings from networks trained on building data. Zmeureanu [68] proposed a method using the general regression neural networks to evaluate the Coefficient of Performance (COP) of existing rooftop units. Yalcintas presented an ANN-based benchmarking technique for building energy in tropical climates, focused on predicting a weighted energy use index. The selected buildings are in large variety [69,70].

The input data for the model training can be obtained from on-site measurement, survey, billing collection or simulation. The raw data may have noisy or useless variables, therefore it can be cleaned and reduced before model development. There is much research concerning the data pre-processing technologies. González and Zamarreño [53] predicted short-term electricity load by using two phases of neural networks. The first layer predicts climatic variables, while the second predicts energy usage, which takes the outputs of the first layer as inputs. The same two-phase technology was also used by Yokoyama et al. in predicting cooling load [46]. The trend and periodic change were first removed from data, and then the converted data was used as the main input for the model training. Additional inputs, including air temperature and relative humidity, were considered to use predicted values. Their effects on the prediction of energy demand were also investigated in this work.

Ben-Nakhi and Mahmoud [48] predicted the cooling load profile of the next day, and the model was trained on a single variable, outside dry-bulb temperature. Ekici and Aksoy [43] predicted building heating loads without considering climatic variables. The networks were trained by only three inputs, transparency ratio, building orientation and insulation thickness. Kreider and Haberl [71] predicted the nearest future with the input of nearest past data. For predicting far future, they used recurrent neural networks. Yang et al. [72] used accumulative and sliding window methods to train neural networks for the purpose of on-line building energy prediction. Sliding window constrained input samples in a small range.

Olofsson et al. [44] used PCA to reduce the variable dimension before predicting the annual heating demand. In their later work, they achieved long-term energy demand prediction based on short-term measured data [45]. Kubota et al. [73] used genetic algorithm for the variable extraction and selection on measured data, and then fuzzy neural networks were developed for the building energy load prediction. Here the variable extraction means translating original variables into meaningful information that is used as input in the fuzzy inference system. Hou et al. [56] integrated rough sets theory and a neural network to predict an air-conditioning load. Rough sets theory was applied to find relevant factors influencing the load, which were used as inputs in a neural network to predict the cooling load. Kusiak et al. [74] predicted daily steam load of buildings by a neural network ensemble with five Multi-Layer Perceptrons (MLPs) methods since in several case studies, it outperforms 9 other data mining algorithms, including CART, CHAID, exhaustive CHAID, boosting tree, MARSplines, random forest, SVM, MLP, and k-NN. A correlation coefficient matrix and the boosting tree algorithm were used for variable selection. Karatasou et al. [6] studied how statistical procedures can improve neural network models in the prediction of hourly energy loads. The statistical methods, such as hypothesis testing, information criteria and cross validation, were applied in both inputs pre-processing and model selection. Experimental results demonstrated that the accuracy of the prediction is comparable to the best results reported in the literature.

The outputs of neural networks may not be exactly what we expected, Kajl et al. proposed a fuzzy logic to correct the outputs by post-processing the results of neural networks. The fuzzy assistant allows the user to determine the impact of several building parameters on the annual and monthly energy consumption [75,76].

Some comparisons between neural network and other prediction models were performed in the research. Azadeh et al. [54] showed that the neural network was very applicable to the annual electricity consumption prediction in manufacturing industries where energy consumption has high fluctuation. It is superior to the conventional non-linear regression model through ANalysis of VAriance (ANOVA). Aydinalp et al. [58] showed that neural networks can achieve higher prediction performance than engineering models in estimating Appliance, Lighting and space Cooling (ALC) energy consumption and the effects of socio-economic factors on this consumption in the Canadian residential sector. Later, ANN was compared with CDA method in [37]. From this work we see that CDA has the ability in solving the same problem as high as ANN model, while the former is easier to develop and use. Neto [77] compared the elaborate engineering method with neural network model for predicting building energy consumption. Both models have shown high prediction accuracy, while ANN is slightly better than the engineering model in the short-term prediction.

2.4. Support vector machines

SVMs are increasingly used in research and industry. They are highly effective models in solving non-linear problems even with small quantities of training data. Many studies of these models were conducted on building energy analysis in the last five years.

Dong et al. [78] first applied SVMs to predict the monthly electricity consumption of four buildings in the tropical region. Three years' data was trained and the derived model was applied to one year's data to predict the landlord utility in that year. The results showed good performances of SVMs on this problem.

Lai et al. [79] applied this model on one year's electricity consumption of a building. The variables include climate variations. In their experiments, the model was derived from one year's performance and then tested on three months' behavior. They also tested the model on each daily basis dataset to verify the stability of this approach during short periods. In addition, they added perturbation manually to a certain part of the historical performance and used this model to detect the perturbation by examining the change of the contributing weights.

Li et al. [80] used SVMs to predict the hourly cooling load of an office building. The performance of the support vector regression is better than the conventional back propagation neural networks. Hou and Lian [81] also used SVMs for predicting cooling load of the HVAC system. The result shows that SVMs are better than the ARIMA model.

All the above work demonstrates that SVMs can perform well in predicting hourly and monthly building energy. However, their experiments were performed on a small number of buildings and their work focused on the prediction of future energy consumption. To investigate the influence of building characteristics on the model performance, Zhao and Magoulès [82] trained the SVM model on multiple buildings' heating load and tested it on the load data of a completely new building. Since the training data size from multiple buildings is very large, the model training process would become extremely slow. Therefore, parallel SVM was applied to accelerate the model training [82,83].

Li et al. [84] predicted the annual electricity consumption of buildings by back propagation neural networks, RBF neural networks, general regression neural networks and SVMs. They found that general regression neural networks and SVMs were more applicable to this problem compared to other models. Furthermore, SVM showed the best performance among all prediction models. The models were trained on the data of 59 buildings and tested on 9 buildings.

Liang and Du [7] presented a cost-effective fault detection and diagnosis method for HVAC systems by combining the physical model and a SVM. By using a four layer SVM classifier, the normal condition and three possible faults can be recognized quickly and accurately with a small number of training samples. Three major faults are recirculation damper stuck, cooling coil fouling/block and supply fan speed decreasing. The indicators are the supply and mixed air temperatures, the outlet water temperature and the valve control signal.

Certain research was performed for pre- or post-process model training. Zhao and Magoulès [85] reduced the variables for SVMs training based on practical considerations and the evaluation results of two numerical methods: correlation coefficient and regression gradient guided feature selection. Lv et al. [86] used PCA to reduce variables before training SVMs for predicting building cooling load. Li et al. [87] used an improved PCA, called Kernel Principal Component Analysis (KPCA), before training SVMs to predict building cooling load. Li et al. [88] used fuzzy C-mean clustering algorithm to cluster the samples according to their degree of similarity. Then they applied a fuzzy membership to each sample to indicate its contribution to the model. In the post-processing, Zhang and Qi [89] applied Markov chains to do further interval forecasting after prediction of building heating load by SVMs.

2.5. Grey models

When the information of one system is partially known, we call this system a grey system. The grey model can be used to analyze building energy behavior when there is only incomplete or uncertain data. Very little work has been done regarding this model.

In 1999, Wang et al. applied a grey model to predict building heat moisture system. The predicting accuracy is fairly high [90]. Guo et al. [91] used an improved grey system to predict the energy consumption of heat pump water heaters in residential buildings. They evaluated the influence of data sample interval in the prediction accuracy and found that the best interval is four weeks. This model requires little input data and the prediction error is within a normal range. Zhou et al. [92] did on-line prediction of cooling load by integrating two weather prediction modules into a simplified building thermal load model which is developed in [5], one is the temperature/relative humidity prediction which is achieved by using a modified grey model, the other is solar radiation prediction using a regression model. Experimental results showed that the performance of the simplified thermal network model is improved as long as the predicted weather data from the first module is used in the training process.

3. Discussion and prospects

From the above description and analysis, it is obvious that a large number of calculations are needed to evaluate the building energy system, from sub-system level to building level and even regional or national level. Each model has its own advantages in certain cases of applications. The engineering model shows large variations. Many considerations can be involved in developing this model. It can be a very elaborate, comprehensive model which is applicable for accurate calculations. In contrast, by adopting some simplifying strategies, it can become a light-weight model and is easy to develop while maintaining accuracy. A commonly accepted drawback of this detailed engineering model is that it is difficult to perform in practice due to its high complexity and the lack of input information. The statistical model is relatively easy to develop but its drawbacks are also obvious, that are inaccuracy and lack of flexibility. ANNs and SVMs are good at solving non-linear problems, making them very applicable to building energy prediction. They can give highly accurate prediction as long as model selection and parameters setting are well performed. SVMs show even more superior performance than ANNs in many cases [84]. The disadvantages of these two types of models are that they require sufficient historical performance data and are extremely complex. The comparative analysis of these commonly used models is summarized in Table 1. We note that this is just a rough summary since each model has large uncertainty or variations and is still being developed.

The prediction of building energy consumption has attracted much attention from the research community, however, there are still many open, unsolved research problems. The future investigations may focus on the following points.

- Develop new and more effective, robust, reliable and efficient prediction models.
- Refine elements of system level energy consumption, compare candidate models and choose the best model for each component.
- Apply energy prediction to the Building Energy Management System (BEMS) to achieve mutual benefits.
- Study artificial intelligence models in these applications, optimize parameters for accurate prediction.

Table 1
Comparative analysis of the commonly used methods for the prediction of building energy consumption.

Methods	Model complexity	Easy to use	Running speed	Inputs needed	Accuracy
Elaborate eng.	Fairly high	No	Low	Detailed	Fairly high
Simplified eng.	High	Yes	High	Simplified	High
Statistical	Fair	Yes	Fairly high	Historical data	Fair
ANNs	High	No	High	Historical data	High
SVMs	Fairly high	No	Low	Historical data	Fairly high

- Evaluate the influence of each variable on empirical models, balance the model performance and feasibility in practice.
- Establish databases and collect precise and sufficient historical consumption data from various cases for further research use.

4. Conclusion

This paper reviews the recent work on prediction of building energy consumption. Due to the complexity of building energy behavior and the uncertainty of the influencing factors, many models were proposed for this application aiming at accurate, robust and easy-to-use prediction. Elaborate and simplified engineering methods, statistical methods, artificial intelligence, especially neural networks and support vector machines, are widely used models. Research mainly concentrates on applying these models to new predicting problems, optimizing model parameters or input samples for better performance, simplifying the problems or model development, comparing different models under certain conditions. Each model is being developed and has its advantages and disadvantages, therefore it is difficult to say which one is better without complete comparison under the same circumstances. However, artificial intelligence is developing rapidly, many new and more powerful technologies developed in this field may bring alternatives or even breakthroughs in the prediction of building energy consumption. Some possible research points are proposed in the paper.

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